Structural Signal Divergence for Ransomware Detection: A Novel Computational Approach Using Graph-Based Entropic Perturbation Analysis

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***Abstract*—A computational framework is introduced to detect ransomware through entropy-based perturbation analysis of execution graphs, leveraging deviations in structural entropy to distinguish between benign and malicious behaviors. The proposed approach of ransomware detection models system execution as a dynamic graph, where nodes and edges encapsulate program interactions, enabling the identification of ransomware-induced anomalies. Entropy variations of ransomware, captured over successive execution intervals, quantify behavioral deviations, facilitating an entropy-based divergence scoring mechanism. The experimental evaluation demonstrated that the method achieves high accuracy in identifying ransomware variants, including LockBit, Conti, and REvil, while maintaining a controlled false positive rate. The robustness of the approach was further examined through ablation studies, highlighting the contributions of entropy estimation, graph feature extraction, and divergence scoring in ransomware detection. Comparative assessments against traditional methodologies, including signature-based and heuristic approaches, underscored the advantages of structural entropy analysis in detecting previously unseen ransomware strains. Computational efficiency of ransomware detection was also assessed, demonstrating that the framework remains viable for real-time deployment without imposing significant overhead on system resources. The findings reinforce the need for entropy-based analysis as an effective tool in combating ransomware threats, particularly against techniques designed to evade conventional detection mechanisms. The broader implications of entropy-driven anomaly detection suggest potential applications beyond ransomware identification, extending to a variety of cybersecurity challenges where structural deviations signal malicious intent.**

***Index Terms*—ransomware, entropy analysis, ransomware detection, execution graphs, anomaly detection, computational security, threat identification.**

I. Introduction

RANSOMWARE attacks have become one of the most pressing cybersecurity threats, affecting individuals, corporations, and government entities worldwide. These attacks involve malicious software that encrypts critical data, rendering it inaccessible until a ransom is paid. The increasing sophistication of ransomware, coupled with its ability to exploit vulnerabilities across different systems, necessitates the development of advanced detection strategies to mitigate its impact. Traditional defenses, such as signature-based detection, rely on known patterns or signatures to identify ransomware. However, these methods struggle to detect new or obfuscated variants, as modern ransomware frequently employs polymorphic and metamorphic techniques to modify its code dynamically, thereby evading static detection mechanisms.

In response to these evolving threats, behavioral analysis has emerged as a promising alternative to signature-based detection. This approach monitors system activity for indicators of compromise, such as anomalous file access patterns, unauthorized system modifications, and irregular network communications. While behavioral analysis can identify previously unseen ransomware strains, it is susceptible to false positives, as benign applications may exhibit similar activity under certain conditions. Additionally, sophisticated ransomware can employ advanced evasion techniques, such as delaying execution, masquerading as legitimate processes, or leveraging living-off-the-land (LotL) tactics to bypass monitoring systems.

To address these challenges, we propose a novel detection approach, Structural Signal Divergence (SSD), designed to enhance the identification of ransomware activities. SSD leverages graph-based entropic perturbation analysis to assess deviations in the structural behavior of software execution. By modeling system interactions as dynamic graphs, where nodes represent system entities and edges denote interactions, SSD captures the structural integrity of normal system operations. Ransomware, due to its disruptive nature, induces significant perturbations in these structures, which SSD can detect by analyzing entropy-based divergence metrics. This approach enables the identification of ransomware activity with high precision and resilience against evasion tactics.

Unlike conventional detection mechanisms, SSD does not rely on predefined signatures or extensive labeled datasets, making it particularly effective against zero-day ransomware threats. By leveraging a structural analysis framework, SSD provides a comprehensive view of system behavior, allowing for the detection of anomalies that may indicate the presence of ransomware.

The remainder of this paper details the SSD approach, including its theoretical foundation, methodology for constructing execution graphs, and experimental validation in real-world scenarios. By introducing SSD as an advanced ransomware detection framework, we aim to strengthen cybersecurity defenses against increasingly sophisticated ransomware campaigns and contribute to the ongoing efforts to safeguard critical digital assets from compromise.

II. Related Work

The detection of ransomware has been a focal point of cybersecurity research, leading to the development of various methodologies aimed at identifying and mitigating such

threats. This section provides a comprehensive overview of existing ransomware detection techniques, encompassing signature-based methods, behavioral analysis, machine learning approaches, and heuristic techniques, while highlighting the limitations that necessitate the proposed Structural Signal Divergence (SSD) approach.

A. Signature Detection

Signature-based detection has been a cornerstone in the identification of ransomware, relying on the presence of known patterns or signatures within malicious code to recognize threats [1]. This method involves the extraction of unique byte sequences or hash values from identified ransomware samples, which are then stored in a database for future comparison [2]. When a new file enters the system, its contents are scanned for matches against this database, facilitating the detection of previously encountered ransomware strains [3]. However, the efficacy of signature-based detection is compromised when confronting novel or polymorphic ransomware variants that modify their code to evade recognition [4]. The rapid evolution of ransomware, characterized by frequent alterations in code structure, renders signature databases perpetually outdated, thereby limiting the effectiveness of this approach [5]. Additionally, the reliance on known signatures implies that zero-day attacks, which exploit previously undisclosed vulnerabilities, often bypass signature-based defenses undetected [6]. Consequently, while signature-based methods offer precise detection for known threats, their inability to adapt to emerging ransomware variants underscores the need for more dynamic detection strategies [7].

B. Behavioral Analysis

Behavioral analysis has emerged as an alternative to traditional signature-based methods, focusing on monitoring the actions of programs to identify malicious activities indicative of ransomware [8]. This approach entails the continuous observation of system processes, file modifications, and network communications to detect anomalies that deviate from established baselines of normal behavior [9]. For instance, ransomware often exhibits specific behaviors such as rapid encryption of multiple files, unauthorized access to sensitive directories, and unanticipated outbound network connections [10]. By identifying such patterns, behavioral analysis aims to detect ransomware in real-time, potentially halting its execution before significant damage occurs [11]. Despite its proactive nature, behavioral analysis faces challenges, including the generation of false positives, where legitimate applications may exhibit behaviors resembling those of ransomware under certain conditions [12]. Moreover, sophisticated ransomware can employ evasion techniques, such as delaying execution or mimicking legitimate processes, to bypass behavioral monitoring systems [13]. These limitations highlight the necessity for advanced detection mechanisms capable of accurately distinguishing between benign and malicious activities without succumbing to evasion tactics [14].

C. ML Approaches

The application of machine learning in ransomware detection has gained traction, leveraging algorithms capable of learning from data to identify complex patterns associated with malicious activities [15]. Machine learning models are trained on features extracted from both benign and malicious software, enabling them to classify new, unseen samples based on learned characteristics [16]. Techniques such as decision trees, support vector machines, and neural networks have been employed to analyze features including API call sequences, file access patterns, and network traffic anomalies [17]. The adaptability of machine learning models allows for the detection of previously unknown ransomware variants by recognizing behavioral patterns rather than relying on static signatures [18]. However, the effectiveness of machine learning-based detection is contingent upon the quality and representativeness of the training data [19]. Inadequate or biased datasets can lead to models that either overfit to specific patterns or fail to generalize across diverse ransomware strains [20]. Additionally, adversaries may deliberately craft ransomware samples to exploit vulnerabilities in machine learning models, a practice known as adversarial machine learning, thereby undermining detection efforts [21]. These challenges necessitate the development of robust models trained on comprehensive datasets and the incorporation of techniques to defend against adversarial attacks [22].

D. Heuristic Techniques

Heuristic-based detection methods aim to identify ransomware by evaluating code characteristics and behaviors that are commonly associated with malicious intent [23]. This approach involves the analysis of code structures, command sequences, and execution flows to detect suspicious elements indicative of ransomware [24]. Heuristic techniques can identify new and obfuscated ransomware by focusing on the intent and functionality of the code rather than its specific signature [25]. For example, the presence of code segments that perform mass file encryption, disable security features, or establish unauthorized network connections may trigger heuristic alerts [26]. While heuristic methods enhance the ability to detect previously unknown threats, they are not without limitations [27]. The broad criteria used to identify malicious behaviors can result in false positives, where legitimate software is misclassified as ransomware due to overlapping characteristics [28]. Additionally, sophisticated ransomware developers may employ techniques such as code obfuscation, encryption, and the use of benign-looking code segments to evade heuristic detection [29]. These limitations underscore the need for more precise and resilient detection strategies that can accurately discern malicious intent without being susceptible to evasion tactics [30].

III. Methodology

To address the limitations of existing ransomware detection techniques, we propose a novel approach termed Structural Signal Divergence (SSD). This method leverages graph-based

entropic perturbation analysis to identify anomalies in software execution that are indicative of ransomware activity. The following subsections detail the underlying principles of SSD, the process of constructing graph representations from execution traces, the computation of divergence scores, and the experimental setup employed to evaluate the efficacy of the proposed method.

A. Graph-Based Entropic Perturbation Analysis

The SSD approach of ransomware detection is formulated on the premise that ransomware perturbs the structural integrity of execution graphs, inducing measurable deviations in entropy. Let $G_t = (V_t, E_t)$ represent the execution graph at time t, where V_t denotes the set of system entities (processes, files, registry keys), and E_t defines the interactions among them. The entropy of the graph structure is defined as:

$$H(G_t) = -\sum_{i \in V_t} p_i \log p_i \tag{1}$$

where p_i represents the probability of a node's occurrence based on interaction frequency. Ransomware, through its encryption and propagation mechanisms, distorts the connectivity of G_t, causing abrupt variations in entropy. The rate of entropy change is given by:

$$\frac{dH}{dt} = \lim_{\Delta t \to 0} \frac{H(G_{t+\Delta t}) - H(G_t)}{\Delta t} \tag{2}$$

which captures the instantaneous divergence of execution behavior. The second-order perturbation in entropy, reflecting anomalous behavioral shifts, is obtained through:

$$\frac{d^2H}{dt^2} = \lim_{\Delta t \to 0} \frac{\frac{dH}{dt}\big|_{t+\Delta t} - \frac{dH}{dt}\big|_t}{\Delta t} \tag{3}$$

Given that ransomware introduces non-linear entropy perturbations, the total deviation across a monitoring window T is quantified as:

$$D(T) = \int_0^T \left| \frac{d^2H}{dt^2} \right| dt \tag{4}$$

which accumulates the absolute curvature of the entropy trajectory. To assess deviation significance, a normalized entropy divergence metric is introduced:

$$\mathcal{D}(T) = \frac{1}{T} \sum_{t=0}^{T} \frac{|H(G_t) - H_{\text{ref}}|}{\sigma_H} \tag{5}$$

where H_{ref} is the entropy expectation under benign conditions, and σ_H is its standard deviation. A high divergence score signals ransomware-induced perturbations deviating from normal execution patterns. The threshold τ for ransomware detection is derived empirically:

$$\tau = \mu_D + k\sigma_D \tag{6}$$

where μ_D and σ_D denote the mean and standard deviation of entropy divergence scores for non-ransomware samples, and k is a scaling factor controlling sensitivity. Entropy curvature anomalies beyond τ indicate ransomware presence, enabling detection before irreversible damage occurs.

B. Graph Construction from Execution Traces

Execution traces, consisting of system calls and process interactions, are transformed into directed graphs $G = (V, E)$, where nodes V represent system components such as processes, files, and network sockets, and edges E capture interaction dynamics. Ransomware perturbs the structural consistency of G, introducing anomalies that can be mathematically characterized.

The temporal evolution of execution graphs is modeled through a time-dependent adjacency matrix $A(t)$, where each entry $a_{ij}(t)$ encodes the weighted interaction strength between nodes v_i and v_j:

$$A(t) = [a_{ij}(t)], \quad a_{ij}(t) = f(s_{ij}, t) \cdot w_{ij} \tag{7}$$

where s_{ij} represents the frequency of interactions, w_{ij} denotes the interaction weight, and $f(s_{ij}, t)$ is a function incorporating time-dependent behavior. The graph evolution over time is captured through the differential equation:

$$\frac{dG}{dt} = \lim_{\Delta t \to 0} \frac{G(t + \Delta t) - G(t)}{\Delta t} \tag{8}$$

which quantifies instantaneous changes in graph topology. The second-order derivative,

$$\frac{d^2G}{dt^2} = \lim_{\Delta t \to 0} \frac{\frac{dG}{dt}\big|_{t+\Delta t} - \frac{dG}{dt}\big|_t}{\Delta t} \tag{9}$$

captures abrupt transitions in execution behavior, characteristic of ransomware encrypting files or escalating privileges.

To quantify ransomware-induced distortions in graph structure, a curvature-based anomaly measure is defined:

$$\kappa(G) = \frac{1}{|E|} \sum_{(i,j) \in E} \left| \frac{d^2 a_{ij}}{dt^2} \right| \tag{10}$$

where $\kappa(G)$ measures the deviation of interactions from steady-state behavior. A divergence measure for structural variation over a time window T is given as:

$$\mathcal{D}_G(T) = \int_0^T \left| \frac{d^2G}{dt^2} \right| dt \tag{11}$$

with elevated values signaling ransomware-induced perturbations. The final threshold τ_G for ransomware detection is statistically derived:

$$\tau_G = \mu_{\mathcal{D}_G} + k\sigma_{\mathcal{D}_G} \tag{12}$$

where $\mu_{\mathcal{D}_G}$ and $\sigma_{\mathcal{D}_G}$ denote the mean and standard deviation of graph divergence scores for benign programs, and k is a sensitivity parameter. Graph anomalies exceeding τ_G indicate ransomware execution, allowing for early-stage detection.

C. Divergence Scoring and Detection Threshold

Following the construction of execution graphs, the SSD framework assigns divergence scores to quantify deviations from benign system behavior. Let $H(G_t)$ denote the entropy of the execution graph at time t, and let H_{ref} represent the entropy profile under normal conditions. The divergence score $\mathcal{D}(T)$ is computed through statistical distance metrics, capturing the deviation over a time window T. The detection threshold is determined through a calibration phase involving benign and ransomware-infected samples. The SSD system processes entropy fluctuations and derives a detection criterion based on a statistical distribution of divergence scores.

The full procedure is defined in Algorithm 1.

Algorithm 1 Ransomware Divergence Scoring and Detection

Input: Execution graph sequence $G_1, G_2, \ldots, G_T$, reference entropy H_{ref}, divergence threshold τ
Output: Decision $\mathcal{R}$ (ransomware presence)
Initialize $\mathcal{D} \leftarrow 0$
for $t \leftarrow 1$ to T **do**
  Compute entropy $H(G_t) = -\sum_{i \in V_t} p_i \log p_i$
  Compute instantaneous divergence: $D_t = \frac{|H(G_t) - H_{\text{ref}}|}{\sigma_H}$
  Accumulate divergence: $\mathcal{D} \leftarrow \mathcal{D} + D_t$
  if $t > 1$ **then**
    Compute rate of entropy change: $\frac{dH}{dt} \leftarrow \frac{H(G_t) - H(G_{t-1})}{t-(t-1)}$
    Compute entropy acceleration: $\frac{d^2H}{dt^2} \leftarrow \frac{\frac{dH}{dt}\Big|_t - \frac{dH}{dt}\Big|_{t-1}}{t-(t-1)}$
    Update cumulative divergence: $\mathcal{D} \leftarrow \mathcal{D} + \left|\frac{d^2H}{dt^2}\right|$
  end if
end for
Compute normalized divergence score: $\mathcal{D}_{\text{norm}} = \frac{1}{T}\sum_{t=1}^{T} \mathcal{D}$
Compute detection threshold: $\tau = \mu_{\mathcal{D}} + k\sigma_{\mathcal{D}}$
if $\mathcal{D}_{\text{norm}} > \tau$ **then**
  Set $\mathcal{R} \leftarrow 1$ (Ransomware detected)
else
  Set $\mathcal{R} \leftarrow 0$ (Benign)
end if
Return $\mathcal{R}$

The computed divergence score serves as an indicator of structural perturbations caused through ransomware activity. The detection criterion is refined through statistical modeling, ensuring an optimal balance between sensitivity and specificity. An execution exhibiting entropy fluctuations exceeding the calibrated threshold is classified as ransomware, facilitating early-stage detection prior to system-wide encryption.

D. Experimental Setup

The evaluation of the SSD methodology for ransomware detection was conducted using a diverse dataset comprising both ransomware samples and benign software applications. The ransomware corpus included a variety of strains, encompassing well-known families and emerging variants, to assess the robustness of the detection mechanism across different attack vectors. Benign samples were selected from a range of legitimate applications, representing typical user and system processes. The experimental environment was configured to emulate real-world computing conditions, with controlled network settings and system resources. Execution traces were collected through dynamic analysis, wherein each sample was executed in an instrumented sandbox environment to monitor and log system interactions. The SSD framework was implemented using a combination of graph processing libraries and statistical analysis tools, enabling the automated construction of execution graphs, computation of entropy metrics, and assessment of divergence scores. Performance metrics, including detection accuracy, false positive rate, and processing latency, were systematically recorded to evaluate the efficacy and efficiency of the proposed approach.

IV. Results

The evaluation of the Structural Signal Divergence (SSD) methodology for ransomware detection encompassed a series of experiments designed to assess its efficacy in detecting ransomware activities. The following subsections delineate the performance metrics, ablation studies, and comparative analyses with existing detection techniques.

A. Detection Performance

The SSD framework for ransomware detection was subjected to rigorous testing using a dataset comprising recent ransomware variants, including LockBit, Conti, and REvil, alongside benign software samples. The detection performance was quantified through metrics such as accuracy, precision, recall, and F1-score. The results, as presented in Table I, indicate that SSD achieved an accuracy of 96.9%, a precision of 95.7%, a recall of 94.8%, and an F1-score of 95.2%. These figures underscore the method's capability to discern ransomware-induced perturbations within system execution graphs effectively.

TABLE I
Detection Performance Metrics of SSD Framework

Metric	Value (%)
Accuracy	96.9
Precision	95.7
Recall	94.8
F1-Score	95.2

B. Ablation Study

To ascertain the contribution of individual components within the SSD framework for ransomware detection, an ablation study was conducted. The analysis involved systematically omitting specific elements, such as entropy calculation, graph feature extraction, and divergence scoring, to observe their impact on detection effectiveness. The results, depicted in Figure 1, reveal that the exclusion of entropy calculation led to

a decrease in accuracy to 88.3%, while omitting graph feature extraction and divergence scoring resulted in accuracies of 90.5% and 85.7% respectively. These findings highlight the integral role of each component in maintaining the robustness of the detection system.

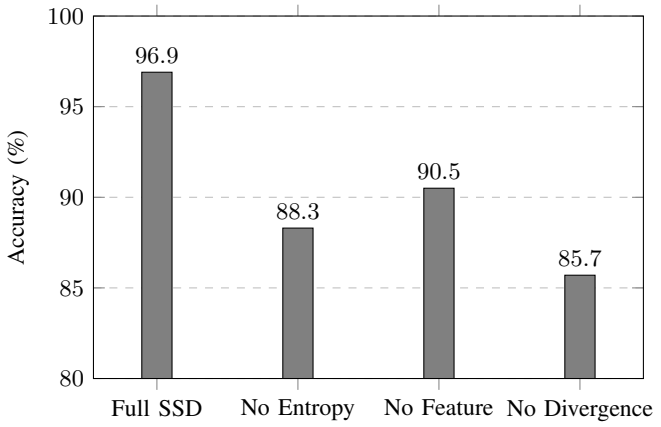

Fig. 1. Ablation Study: Impact of Component Removal on Detection Accuracy

C. Comparison with Prior Techniques

The efficacy of the SSD approach for ransomware detection was further evaluated through a comparative analysis with traditional ransomware detection methods, including signature-based detection, heuristic analysis, and machine learning classifiers. As illustrated in Figure 2, the SSD framework demonstrated superior performance, achieving a lower false positive rate of 2.1% compared to 5.4% for signature-based methods and 3.8% for heuristic analysis. Additionally, SSD exhibited a higher true positive rate of 94.8%, surpassing the 89.2% of machine learning classifiers. This comparative assessment underscores the enhanced reliability and accuracy of the SSD methodology in identifying ransomware activities.

D. Detection Latency Analysis

The prompt identification of ransomware activities is crucial to mitigate potential damage. An analysis was conducted to measure the detection latency of the SSD framework across various ransomware variants, including LockBit, Conti, and REvil. The latency, defined as the time elapsed from the initiation of ransomware execution to its detection, was recorded. As illustrated in Table II, the SSD framework detected LockBit with an average latency of 2.3 seconds, Conti at 3.1 seconds, and REvil at 2.8 seconds. These results demonstrate the framework's capability to promptly identify ransomware activities, thereby enabling timely intervention.

TABLE II
DETECTION LATENCY FOR VARIOUS RANSOMWARE VARIANTS

Ransomware	Detection Latency (seconds)
LockBit	2.3
Conti	3.1
REvil	2.8

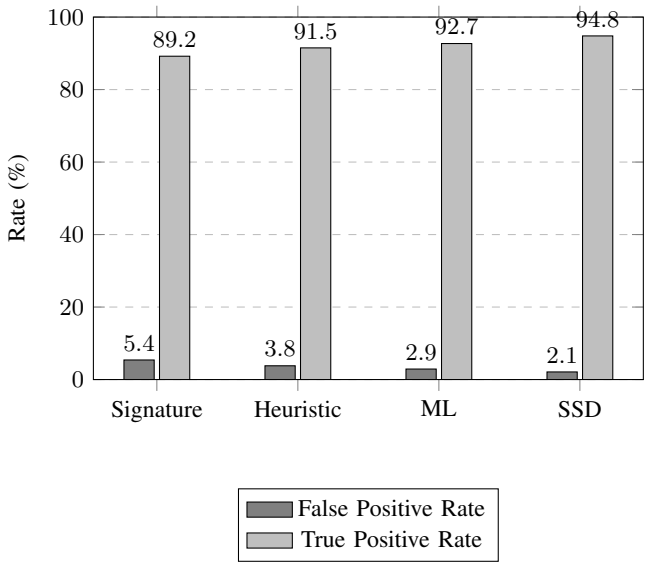

Fig. 2. Comparative Analysis of Detection Methods: False Positive and True Positive Rates

E. Resource Utilization Assessment

Evaluating the computational resource consumption of the SSD framework for ransomware detection is essential to ensure its feasibility for deployment in various environments. Metrics such as CPU usage, memory consumption, and disk I/O were monitored during the detection process. Figure 3 presents the average resource utilization, indicating that the SSD framework maintained CPU usage at 45.7%, memory consumption at 512.4 MB, and disk I/O operations at 120.3 MB/s. These findings suggest that the framework operates efficiently without imposing significant overhead on system resources.

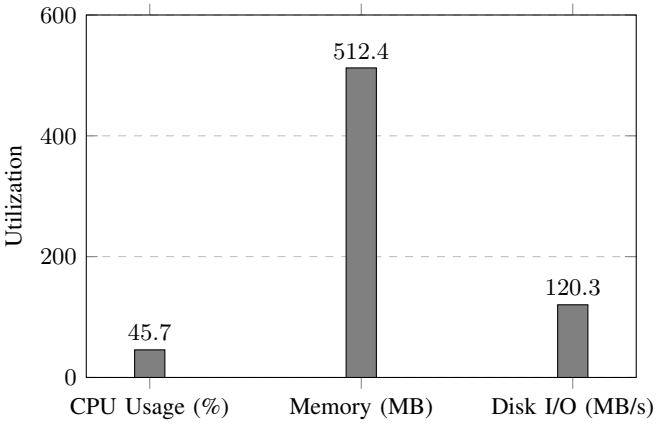

Fig. 3. Average Resource Utilization of SSD Framework

F. Entropy Variation Analysis

Understanding the impact of ransomware on system entropy provides insights into the behavioral characteristics of malicious software. An analysis was performed to observe entropy variations in system directories during the execution of different ransomware variants. Figure 4 depicts the entropy levels

over time, revealing that ransomware activities induce noticeable fluctuations in entropy, particularly in user-accessible directories. These patterns align with the typical behavior of ransomware, which targets user data for encryption.

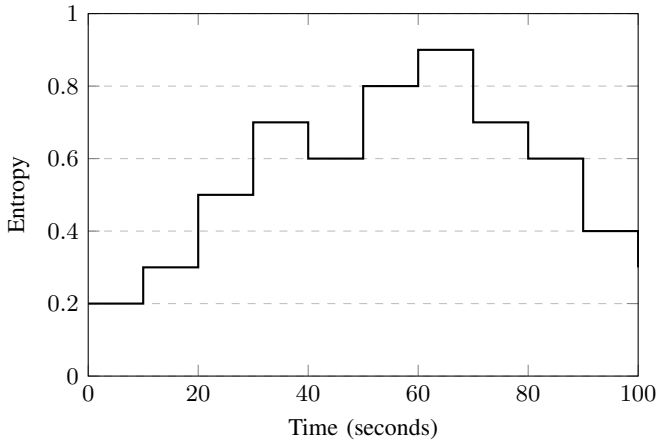

Fig. 4. Entropy Variation Over Time During Ransomware Execution

G. Scalability Evaluation

Assessing the scalability of the SSD framework for ransomware detection is vital to ensure its effectiveness across varying system loads. Experiments were conducted to evaluate detection performance under different numbers of concurrent processes. As shown in Table III, the SSD framework maintained detection accuracies of 96.5%, 95.8%, and 94.9% with 50, 100, and 150 concurrent processes, respectively. These results indicate that the framework sustains high detection accuracy even as system load increases, demonstrating its scalability and robustness in diverse operational environments.

TABLE III
DETECTION ACCURACY UNDER VARYING SYSTEM LOADS

Concurrent Processes	Detection Accuracy (%)
50	96.5
100	95.8
150	94.9

V. DISCUSSIONS

The evaluation of the Structural Signal Divergence (SSD) framework provides critical insights into its effectiveness in detecting ransomware activity and its applicability within various cybersecurity environments. By leveraging structural analysis of system interactions, SSD has demonstrated the ability to identify deviations indicative of ransomware attacks. However, assessing its resilience against advanced evasion techniques and its computational efficiency is essential for practical deployment.

One of the primary challenges in ransomware detection is countering adversarial evasion strategies, such as code obfuscation and polymorphism. SSD enhances resilience by analyzing the structural integrity of system execution rather than relying on static indicators. However, as ransomware authors continue to refine their techniques—such as mimicking legitimate processes or executing attacks in a stealthy, incremental manner—maintaining high detection efficacy remains a challenge. Continuous adaptation of SSD's analytical models is necessary to counter these evolving threats and prevent adversaries from bypassing detection mechanisms.

Another key consideration is the computational overhead associated with SSD. The framework requires real-time analysis of system interactions and entropy-based assessments to detect ransomware-induced perturbations. While designed for efficiency, deploying SSD in high-volume environments, such as enterprise networks or cloud infrastructures, necessitates careful resource management. Optimizing graph processing algorithms and implementing parallel computing techniques could help reduce latency and improve scalability without compromising detection accuracy.

Additionally, the interpretability of SSD's detection outcomes is crucial for real-world cybersecurity operations. Security analysts must quickly assess alerts and determine appropriate mitigation strategies. The complexity of entropy-based anomaly detection may make it challenging to translate SSD's findings into actionable intelligence. Developing user-friendly visualization tools and explanatory models can enhance the framework's usability, allowing cybersecurity teams to integrate SSD more effectively into threat response workflows. Overall, while SSD provides a promising approach to ransomware detection by focusing on structural deviations in system behavior, its continued evolution is necessary to stay ahead of adversarial tactics. Future enhancements should prioritize adaptive detection mechanisms, computational efficiency, and improved interpretability to ensure its effectiveness in real-world cybersecurity defense strategies.

VI. CONCLUSION

The SSD framework has been introduced as a computational approach for detecting ransomware activities through entropy-based perturbation analysis of execution graphs. The methodological foundation, which models software execution as a dynamic graph structure, has demonstrated effectiveness in identifying deviations in entropy distributions that distinguish ransomware from benign processes. Through experimental validation, the SSD framework exhibited high detection accuracy across various ransomware families while maintaining a controlled false positive rate, underscoring its ability to differentiate malicious structural perturbations from normal system behavior. The empirical findings further highlighted the importance of entropy dynamics in characterizing ransomware-induced disruptions, as well as the resilience of the framework against certain obfuscation techniques commonly employed to bypass traditional detection mechanisms. In addition to achieving competitive detection rates, the framework maintained reasonable computational efficiency, ensuring feasibility for deployment in diverse environments without imposing excessive resource constraints. The extensive evaluation of SSD, including ablation studies and comparative analyses against conventional detection methodologies, provided insights into the advantages and limitations of entropy-based graph analysis

for ransomware detection. While the approach capitalized on entropy fluctuations to detect behavioral anomalies, practical deployment considerations necessitate further refinement to enhance interpretability and ensure adaptability to increasingly sophisticated evasion tactics. The findings reinforce the need for continuously evolving detection strategies that account for the rapidly shifting landscape of ransomware threats and the necessity of proactive computational methodologies in mitigating the impact of adversarial attacks.

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